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BUSINESS ANALYTICS: AN EXPLANATORY REPORT ON THE EVOLUTION OF BUSINESS INTELLIGENT AS AN ADVANTAGE IN THE DECISION-MAKING PROCESS

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SUMMARY

Much has been said about the use of data to support the decision-making process. This article aims to explain which are the phases and assumptions that an organization should observe from the classic business intelligence based on facts that occurred in the past or Business Intelligence (BI) to the most advanced features of Business Analytics (BA) that enables the creation and analysis of future scenarios with the aim of anticipating events, improving the decision-making process and therefore enabling more effective management. The methodology used in the research is phenomenological, which consists of understanding meanings, everyday reports, case studies and observation with exploratory, bibliographical and documental research, based on management and governance models of business organizations. The BA becomes essential for the decision-making process based on data, mitigating the "assumption" factor and directly impacting the organization's performance. Thus, the pertinent question is: what are the necessary steps and assumptions for BI to evolve? Demonstrate how organizations can evolve to a level that allows them to monitor, analyze trends and predictions, directly impacting the decision-making process of organizations. The present work aims to offer a path for the evolution of the decision-making process of organizations based on data and mitigating assumptions in the decision-making process. The results achieved with Business Analytics demonstrate the ability to identify the problem and report it so that the manager can take the necessary measures before it worsens.
Keywords: Business Analytics – Business Intelligence – Decision Process
Palavras-chave: Análise de Negócios – Inteligência de Negócios – Processo Decisório

1. INTRODUCTION

Modern organizations have systematically used analysis and data to gain competitive advantage based on a more assertive and effective decision-making process. GOASDUFF (2020) when analyzing trends in data for 2020 in a Gartner Group report, increasingly listed the unit of data as analysis, describing that the clash between data and analysis will imply an increase in interaction and collaboration between data and analytical functions, impacting the entire the chain involved in the decision-making process, from the people and processes that support them to the technologies and resources provided. DELOITTE research with more than 2000 executives, DELOITTE INSIGHTS (2020), showed that many organizations that are implementing a strategy for industry 4.0 tend to use Analytics, a colloquial way to designate Business Analytics, to connect their organizations and use data to analyze , take action and start learning to better anticipate future scenarios and changes.

In the 1980s, concepts of business intelligence, also known as Business Intelligence (BI), emerged to collect data, organize them and share information from historical facts to aid decision making. However, the growing amount of data available for analysis, facilitated by technologies such as big data, allows the storage and processing of data generated in ever-increasing speed, volume, and variety MARQUESONE (2016), thus bringing a universe of opportunities. According to BROCCHI (2018), in an article by the Mckinsey Global Institute , the main financial institutions that previously used only descriptive analysis, intrinsically linked to BI, to support the decision-making process are now using analysis in products, processes and services, and where they used to build Data relational warehouses to store structured data from specific sources are now operating data lakes with large-scale distributed file systems, working with structured and unstructured data from a wide variety of sources. However, many companies have not yet evolved to an analysis process that goes beyond the capabilities of BI, a fact corroborated by an MIT article by DAVENPORT (2020) in which research results demonstrate that analytical competitors are currently in the minority. However, big data and analytics technologies have been available for several years. this paper emphasizes that there is a multidimensionality of factors that lead an organization to be moved by data and analysis. Another fact refers to the combination of data, tools, talent and culture so that companies can make the most of the insights they obtain and incorporate them into decisions, thus using this entire universe of available data with the objective of predicting and creating future scenarios. The creation of predictions based on facts from the past registered in the BI itself is the technique known as business analytics (BA). Knowing the stages and assumptions of business intelligence (BI) and Analytics is essential for the evolution of a BI system to BA, as BI is a condition for BA and its use allows organizations to anticipate future events, taking more and more right decisions and thus creating competitive advantage. Discovering the necessary steps for this evolution is one way for companies to maintain their competitive advantage in the market.

This article will conceptualize the decision-making process and the types of analyzes involved to assist it. How did the decision-making process based on business intelligence begin and how did it evolve following steps and premises to a process based on data analysis that predicts the future using mathematical models. Understanding these concepts is fundamental for us to know how to seek the best tools to support business decisions, foster competitive approaches and allow companies to know their operational and strategic value.

Data products have been developed by organizations for internal use or being created and sold to the market by companies that have discovered how to use the great potential that data has, earning large sums or saving expressive amounts , among its diversity of applications, also used for decision support. DAVENPORT (2018) comments that "decisions are important for companies that entered this era, but they realized that analysis and data can support not only decisions, but also products and services". The business world is constantly evolving and changes are happening all the time. Business analytics is a term that is part of this race and is helping to lead these transformations. Technology is no longer seen as a mere supporting element in this transformation process, it plays a central role in companies, bringing a series of benefits and competitive advantages. According to PETTEY (2019), in a document by the Gartner Group, reports that we are still in the initial phase of adopting information as an asset for companies , but it is a competitive differentiator for leading organizations that are focusing on digital transformation, in that data and analytics become strategic priorities. In this context, data becomes the main key to digital transformation and in this study it is emphasized that leading organizations in all sectors are using data and analysis in their competitive strategies and predicts that in 2022, 90% of corporate strategies will explicitly announce information as a critical business asset and analytics as a core competency. The journey of evolution from BI to BA brings the benefit of a leap of excellence in the decision-making process, since it supports decisions by "anticipating the future" with the prediction of events, delivering insights and helping to achieve goals, contributing thus ultimately to the increased profitability of the company. Thus, this work intends to answer the following question: how can the migration from a system based on the past business intelligence (BI) to a system based on the future, business analytics (BA) be carried out in contemporary organizations?

This article aims to show the steps for the evolution of a business intelligence process in which we can only have information on the result of past actions (BI), to a system that can predict trends, discover patterns, and prescribe actions to improve the decision-making process (BA).

2. BIBLIOGRAPHICAL REFERENCES

In order to support the discussion of explanations, this chapter presents the theoretical framework of the main themes involved in the article in question.

2.1 Decision-making process

A decision can directly impact the relationship between the success or failure of an enterprise, making decisions based on reliable information, available at the right time and with a high degree of relationship on the subject in question greatly increase the chances of being successful.

Decision is defined in several ways in the administration dictionary by DUARTE (2015), including:

- Choice of tactics and strategy to achieve the objective;
- Definition by one, among several lines of action, aiming to achieve the most efficient and most effective way of achieving the desired objective;
- Taking a position of the leader or management of an organization, based on the interpretation and correct analysis of a line or lines of suggested actions, aiming at the realization of a plan.

The decision-making process can be understood as a process from the identification of the problem, going through the mapping of alternatives until reaching the realization of a choice based on a certain criterion.

Nevertheless, according to RIBEIRO (2015) decisions can be taken from a great weighting on the problem, quickly and inadvertently and even not making any decision.

We invariably need to make decisions, it's a continuous process. New challenges are presented at all times so that managers of organizations can define the direction of their companies. For GOMES (2019), "A decision needs to be made whenever one is faced with a problem that has more than one alternative for its solution".

FONTANILLAS (2014) describe that it was in the Renaissance that the systematic study of decision emerged, amidst the scientific and cultural revolutions that occurred at the time when the studies where the origins of statistics and probability were found, the first mechanisms being mathematics developed with the aim of unveiling the future in a scientific way.

2.2 Types of Analysis

The decision-making process can currently use the enormous amount of data generated at all times by business, relationship, economic, financial, Internet, mobile devices applications, using analysis techniques to transform this data into relevant information and help decision-making . According to DAVENPORT (2018) the analyzes are categorized as descriptive, predictive, prescriptive and autonomous, defined as follows:

- Descriptive Analysis: associated with Business Intelligence (BI), provides access to historical or current information, with the ability to alert, explore and report. Indicates "What happened or is happening?", but does not inform the "why";

- Predictive Analysis: associated with Business Analytics (BA), it uses quantitative techniques and technologies that use past data to review the future. Indicates the "What is most likely to happen?" in the future;

- Prescriptive Analytics: Slightly deeper than Predictive Analytics, it uses a variety of quantitative techniques and technologies to specify ideal behaviors and actions. Indicates "What can happen?" in the future, if a certain decision is taken, identify the best measures to be implemented.;

- Autonomous Analysis (Cognitive): use of artificial intelligence or cognitive technologies to create and improve models and learn from data. Related to knowledge discovery and machine learning.

The Gartner Group lists yet another type of analysis, DIAGNOSTIC ANALYSIS (2020) :

- Diagnostic Analysis: also associated with BI and being a specialization of analysis described as a form of advanced analysis to answer the question "Why did this happen?".

In WILDER's (2015) definition, analytics is "the application of processes and techniques that transform raw data into meaningful information to improve decision-making".

2.3 Business Intelligence (BI) or Business Intelligence

It is a term whose creation is credited to Howard Dresner, when in 1989 he used the word "umbrella" in the Gartner Group for the set of concepts and methods to support decision-making using systems based on facts and dimensions BRAGHITTONI (2017) , the author also points out that Howard Dresner described it as follows "A methodology by which tools are established to obtain, organize, analyze and provide access to the information necessary for decision makers in companies to analyze the phenomena about their businesses". Provides a historical view of facts that occurred in the business environment through a process of collecting, organizing, analyzing, sharing and monitoring information to support management, transforming raw data into relevant information for decision making. According to SHARDA (2019) BI is a term that combines architecture, tools, databases, analytical tools, applications and methodologies so that decision makers obtain valuable insights when analyzing data, situations, historical and current performances. Per Gartner Group alignment, BUSINESS INTELLIGENCE BI (2020) "is an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access and analysis of information to improve and optimize decisions and performance".

2.4 Big Data

It is one of the keys to the evolution of BI to BA since it allows the treatment of a large volume of data, essential for the predictive process, in different ways and with great speed. For MACHADO (2018) "a new wave of technology and architecture aimed at extracting value from an immense variety of data, which allows high speed with the objective of capturing, discovering and analyzing this information and data, in order to transform them into important and valuable information in the field of business management".

2.5 Business Analytics or Business Analysis

It is an expression that has been confused and at the same time has been given as a synonym for Business Intelligence itself, Predictive Analysis, Business Analysis in its direct translation or simply Analytics. What is not confused is that BA has been attributed to the use of data analysis (Data Analytics) through mathematical models for generating and understanding future scenarios for creating value for companies. In the definition of the Gartner Group, BUSINESS ANALYTICS (2020) is a set of solutions used to create analysis models and scenario simulations, understand realities and predict futures using data mining tools, predictive analysis, applied analysis and statistics. Analytics as the extensive use of data, statistical and qualitative analysis, explanatory and predictive models and fact-based management for actions and decision making DAVENPORT (2018).

Both BI and BA drink from the same source, the two concepts are similar, they use the same data to generate information since BA uses the entire historical base generated by BI. However, BA is an evolution of BI, ultimately Business Analytics looks to the future, while Business Intelligence looks to the past, to the rear view.

2.6 General Concepts

2.6.1 Data Structured and Unstructured

Structured data are organized in rigid schemes and suitable for the table format and the unstructured ones do not have a pre-defined format, thus making their storage more complex, they can be presented as videos, images, text formats. There are estimates that 80% of the data available globally are considered unstructured data MARQUESONE (2016).

2.6.2 Data Warehouse

For BARBIERI (2020) it represents a “data warehouse” used to store structurally modified data to meet Business Intelligence (BI) accumulating data over the time dimension, forming a history. A place where there is a controlled accumulation of transactional data, it composes day-to-day corporate transactions, increasing vegetatively with the increment of new organizational facts.

2.6.3 Data Lake

According to BARBIERI (2020) “They are transient deposits that serve to filter, clean and consolidate data, which can normally be sought from different transactional sources, with different formats”. The data lake emerged with the advent of big data, as it allowed the storage of data “in natura”, leaving the treatment for another time. They store a wide spectrum of data types thus increasing the amount of data available for decision making. SAWADOGO (2020) emphasizes that "the data lake is a large repository of raw data that stores and manages all company data in any format", nevertheless, the concept of data lake remains ambiguous or confusing for many researchers and professionals, who they often confuse it with other technologies and especially with the data warehouse.

2.6.4 Etl

According to BARBIERI (2020) “ETL (Extract, Transform and Load) and has a strong data integration bias, but the keyword is quality.” The meaning of this acronym is the ability to transfer via copy the data of the transactional environment, transform them in a way that suits the needs in a prophylactic way, avoiding incomplete elements, insignificant fields and wrong or doubtful data that harm the decision-making process and the execution of the payload to the intelligence environment.

2.6.5 Insights

“INSIGHT” is defined as “Sudden and clear understanding of something; state, light: “Having insight is, suddenly, grasping things, noticing the unnoticed, discovering the obvious, unveiling what is contained beyond the trivial.”.” INSIGHT (2020). It is the value earned using analytics; they are high value ideas for the business as they can be used for its expansion through the glimpse of opportunities.

2.6.6 Digital Transformation or Scanning

According to DAHER (2020) “Digital Transformation (TD) refers to the adoption of digital processes and tools to achieve strategic business goals. It is a complex process that requires a huge cultural change in the organization.”. It is the fact of using technology as a key part of the business, increasing its results, and using the concept throughout the organization.

2.6.7 Data Analyst, Data Science or Data Science

For FAWCETT (2018) Data Analyst is “just another term to designate professionals who are practicing BI in the form of compiling and cleaning data, extracting reports and maybe some visualization”. His skills go through Excel, data query language and report generation. Recognized capabilities with descriptive data analysis or report extraction.

Still according to FAWCETT (2018) data scientists perform predictive analysis, prescriptive analysis, cognitive analysis and more advanced analytical tools and algorithms. These are professionals who preferably should have more in-depth knowledge in programming to be able to write data cleaning and analysis codes, in addition to developing specializations in modeling, experimentation and data analysis.

For FAWCETT (2018) Data Science is “a set of fundamental principles that guide the extraction of knowledge from data”. Involving principles, processes, and techniques to understand phenomena through (automated) data analysis.

2.6.8 Data Mining or Data Mining

For FAWCETT (2018) Data Mining represents the extraction of knowledge from data using technologies for this purpose and completes "As a term, "data science" is often applied more broadly than the traditional use of "data mining", but the Data mining techniques provide some of the clearest examples of data science principles.". Data mining is a process for discovering patterns in large databases, with one of the greatest benefits being the creation of business intelligence on a given subject, also known as: KDD – Knowledge Discovery in Databases (Knowledge Discovery in Databases) HURLEY (2020). According to SHARDA (2019) data warehouses "are very large and resource-rich, and it became necessary to "mine" corporate data to "reveal" new and useful nuggets of knowledge to improve business processes and practices, which gave rise to the terms data mining and text mining".

3. RESEARCH METHODOLOGY

Companies that already have a journey with Business Intelligence can make use of the phased evolution to migrate to the highest degree in Business Analytics. Currently, the most innovative companies have a BA strategy, obtaining insights for decision making. Some assumptions must also be taken into account in a transition strategy from BI to BA.

Such phases and assumptions were raised in a bibliographical and documental study in which a new methodology emerges as a migration strategy, using the phenomenological method that in Vergara's conception (2005) consists of understanding meanings, diaries, daily reports, case studies , observation, content of texts for analysis are the main sources of data for the researcher.

However, the authors used for the research are a reference for the area explained, and the use of literature regarding the BA is still incipient, given that its use is innovative and is characterized as a limitation of the method used. Henceforth, the case study focused on processes provides an understanding of the construction of the studied phenomenon. Finally, we tried to use literature, books, articles, and works that do not offer a generalist focus on IT or financial BI, but on decision-making processes, based on the Minerva platform of the Federal University of Rio de Janeiro and the SCOPUS base.

4. THE EVOLUTION PHASES BETWEEN BI AND BA

4.1 The beginning of everything

In little more than the last decade, Business Analysis, BA, has evolved much more than in the entire period of existence of Business Intelligence or BI. DAVENPORT (2018) classifies the steps and positions organizations in four phases, but mentions that the last three phases emerged from 2007. The first phase, where many companies still find themselves, called “Analysis 1.0” is practiced by organizations that did not evolve their maturity in Analytics and still use BI as it started. For MARQUESONE (2016) the concept of BI began in the 1980s when people began to collect, organize and share information to aid decision-making, BRAGHITTONI (2017) also positions the appearance of the term at the end of the 1980s. SHARDA (2019) considers that the term was coined in the 1990s by the Gartner Group, but highlights that the concept is much older and says that its roots go back to the management information system that generates reports from the 1970s. emergence, BI uses descriptive and diagnostic analysis exploring reports and dashboards with information from events that occurred in the past and their attempt to create trends to predict the future (predictive analysis) or recommend how one can do a better job, (prescriptive analysis) is quite limited, it uses a small fraction of all the potential that the data collected, stored and organized are capable of providing. However, it is still necessary today as it is the basis for the other phases, as predictive and prescriptive analysis uses data from historical facts to envision the future.

still agree with DAVENPORT (2018) sophisticated companies continue to use traditional BI today and it could not be different due to the descriptive basis needed for the other phases, but they try to control its volume and attract users instead of users specializing in analysis to use it. Within this phase, traditional BI itself evolved from reports and dashboards created only by the IT area or by the area or professionals specializing in analysis to BI Self-Service in which the business area user himself can create his analyzes defined as BI of self-service by Gartner Group, SELF SERVICE BUSINESS INTELLIGENCE (2020) Users finals create and deploy their own reports and analytics supported by an architecture and tools appropriate for this purpose. DAVENPORT (2018) calls this set of tools that emerged in this first phase to facilitate the work of “self-service analysis”, giving more freedom and flexibility for users to create mainly visual analysis. However, a challenge of this flexibility and the use of spreadsheets still today as the main analytical tool is the emergence of what DAVENPORT (2018) calls “ multiple versions of the truth ”; mistakes caused by the lack of governance over the data available for use. DAVENPORT (2018) also comments that in this phase “relational data warehouses” or Datawarehoses were used, relational databases that, through a costly and slow process, called ETL, which could perform the task of extracting, transforming and loading the data. With this, data are collected, transformed and organized into a structure what may be used in the future BRAGHITTONI (2017). As the ETL process is very specialized, usually only the

IT area is capable of carrying it out, making it a slow and reactive job .

4.1 The next step – Big data

Just over 10 years ago, great Silicon Valley companies saw the need to capture, organize and understand a huge amount of data from clicks that their customers had produced mainly on Internet pages. But for it to be possible to deal with the large volume, speed and mainly variety that the data presented, it would be necessary to make use of a technology that went beyond the traditional Datawarehouses, incapable of meeting the variety of unstructured data MARQUESONE (2016). Big data, capable of storing a large set of data, made it possible to go one step beyond descriptive analysis , because with a larger volume of data it was possible to develop predictive analysis. For AMARAL (2016) "it is the phenomenon in which data is produced in various formats and stored by a large number of devices and equipment". In the conception of SHARDA (2019) "basically, Big Data is data that cannot be stored in a single unit. It refers to data existing in many different forms: structured, unstructured, in flow, and so on". DAVENPORT (2018) classifies this second phase as "Analysis 2.0" and relates it to these companies pioneers in Silicon Valley that today are among the largest companies in the world. However, it does not recommend that other organizations adopt this approach directly, but it highlights that some lessons are important in "Analysis 2.0". big data is ideal for working with all this large amount, speed and variety of data for organizations, this new technology has allowed predictive and prescriptive analytics to take off mainly due to their volume, "predictive performance continues to improve as more data is collected . used " FAWCETT (2018). For ROGERS (2017) ". These "big data" tools enable companies to make new types of predictions, discover unexpected patterns in business activity and unlock new sources of value."

4.2 Data products - Data becomes strategic

Already in the last decade, according to DAVENPORT (2018), companies come to the conclusion that big data is not just a whim and that they exist important technologies and lessons to be adopted. However, it becomes necessary to combine analysis 1.0 and 2.0, culminating in the analysis 3.0 what DAVENPORT (2018) calls “BIG DATA for large companies” which is the union of small data (small data) indicating how the customers bought in the past and the large volume generated by social media, IoT (Internet of Things) data and customer information. It becomes a matter of ability to analyze all the data . For DAVENPORT (2018) this phase is characterized by the use of data analysis not only for decision making. For the author, the “operational analysis” integrates with the production process and systems, place that the analysis is used to generate decisions with analytical applications for drivers' journeys, performing real-time data analysis on the best route to be used by carriers in logistics. in other areas , marketing campaigns analyze interaction with customers and make offers in real time on the web, the supply chain is also impacted in terms of form and quantity correct number of products to be stored.

For BENGFORT (2019) data products are like “systems that learn with data . They are self-adaptive and highly applicable ”, extracting value from data and generating more information . The author further describes how “capable of discovering individual patterns in the activity human , and products decision - oriented , whose resulting actions and influences are also recorded as new data. In the analysis 3.0 phase of DAVENPORT (2018), data and analysis become essential in many strategies and business models for creating data products that generate billions of dollars in revenue. FAWCETT (2018) mentions how “data analysis projects" that can reach all business units, and that collaborators of these units must interact with the data scientist team to really understand what is happening at company and the employees must have "a fundamental foundation in the principles of data analytic thinking". Still according to FAWCETT (2018) "when faced with a business problem, you must be able to assess whether and how data can improve performance" and relate the phases to assess a business problem in terms of value and divide it in data mining tasks.

a) Understanding of the data

Data are the raw material for the solution that will be built, so it is very important to know the data that are available very well and to know if they are sufficient for the development of the solution in question. As understanding of the data progresses, solution paths can shift in response and team efforts can change. until it splits .

b) Data preparation

not always and most of the time the data is not in the ideal format to be used without any treatment. Therefore, removing or inferring missing values, converting formats, normalizing are necessary tasks for its adequacy.

c) Modeling

In this phase, models or patterns are created to capture regularity in the data. It is at this stage that the main mining techniques are applied, mathematical models are created having as their main source, the algorithms for discovering patterns, rules and associations with data.

d) Assessment

Trust is the key word at this stage, rigorous assessments of the presented result must be carried out to verify that the data and models are valid and reliable . before proceeding. Since it is much easier and cheaper to test the model in a development environment , this phase also help at Ensure that the model meets the organization's business objectives. FAWCETT (2018) corroborates the previous sentence com " remember that the main purpose of data science for business is to support decision making and that we start the process with a focus on the business problem we would like to solve" .

4.2.1 Cognitivity - Automation of analyzes with machine learning

The phase classified as analysis 4.0 by DAVENPORT (2018) is called cognitive analysis, which is what there is currently the most advanced in terms of Business Analytics. In the others three phases the analysis was carried out by one or more people, after all the organization of the data, formation of hypotheses and indication to the computer of what needed to be done. Cognitive analysis, on the other hand, eliminates, or better saying , limits the role of the component human of the equation . DAVENPORT (2018) also indicates that intelligence artificial or Cognitive technologies are widely seen as perhaps the most disruptive technological force facing the world today." For MARR (2017) it is based on machine learning (Machine Learning) and deep learning technology (Deep Learning), allowing computers to learn from data autonomously. Yet using DAVENPORT (2018), there is one variety of different technologies under the "umbrella" of cognitive . They are tools most often based on analysis or models statistics , In machine learning , models are created by the tool itself and validate whether the models fit the data , and being necessary create more models . According to DAVENPORT (2018) in some forms of machine learning, it can be said that models are created by data, a data set trains the model, and it adapts to the new forms. DAVENPORT (2018) emphasizes that the " rise of machine learning is an answer to the rapid growth of data, software availability and the power of computing architecture current ”. For SHARDA (2019) “computerized systems enable people to overcome their cognitive limits by quickly accessing and processing vast amounts of stored information” and that managers need computerized systems to help them in the decision - making, but in many cases such decisions are being automated, eliminating the need for any managerial intervention.

5. PREMISES AND IMPORTANT ACTIONS FOR THE ESTABLISHMENT OF MIGRATION

Much has been said about the importance of data in organizations and how its volume, variety and speed have been growing dramatically, giving rise to solutions with big data. For FAWCETT (2018) data is an important strategic asset, which this view allows you to analyze how much to invest and makes a relationship between the data and the team of professionals needed to extract the best from them. He further reinforces that even the best team of data scientists can generate little value without the right data, and that often the best data cannot improve decision-making without adequate data science talent.

Still according to FAWCETT (2018) “some data will be available practically for free, while others will require an effort to obtain. Some data can be purchased. Still others simply do not exist and will require ancillary projects to organize their collection.”

FAWCETT (2018) comments on the classic story of a small bank in Virginia USA that in the 90s proved the importance of investing in data and the relevance of considering it a strategic asset. In the 1980s, data science transformed the consumer credit industry with default probability modeling, “from personal assessment to large-scale strategies and market share, which brought concomitant savings”. At the time, credit cards practiced uniform prices because companies did not have adequate information systems to work with differentiated prices on a large scale and because the bank's management believed that price discrimination would not be supported by customers. However, Richard Fairbanks and Nigel Morris realized that information technology was already capable of creating a more sophisticated predictive model, but they could not convince the big banks, but they did get the attention of this small regional bank in Virginia. The bank manager was convinced that modeling profitability was the correct strategy and not just the probability of default, it was known that a small slice of customers represented more than 100% of the bank's profit from credit card operations making up a concept the Pareto analysis, since the rest of the customers were either break-even or losing money. They envisioned that by modeling profitability they could make better deals for the best customers. However, the bank had a big issue to be resolved, it did not have the necessary data to model profitability in order to offer different conditions to different customers, in reality nobody did because “banks were offering credit with a specific set of conditions and a standard model”. They only had data related to terms offered in the past and to customers who were judged credible based on the existing model.

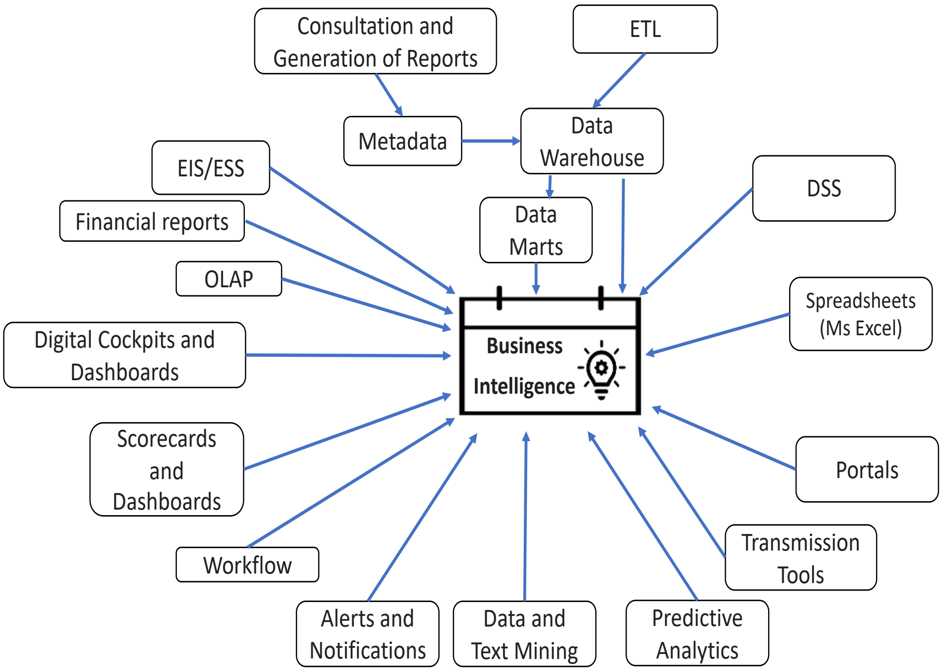
What the bank did was invest in data, getting the data it needed at a fair cost. They started to offer different credit terms to their clients in order to generate the mass of data necessary for the evaluation of the model. Different terms were randomly offered to different customers to run experiments, this eventually led to an increase in the late rate by three percentage points, but it was seen not as a loss, but an investment in data. In this case, losses are the cost of data acquisition. The data analytic thinker needs to consider whether he expects the data to be of sufficient value to justify the investment. At the beginning, the bad quotas increased and the losses continued for some years, although investors complained about them, they persisted in their strategy and it became so profitable that it was spun off into other operations of the bank that, now, were overshadowing the success of consumer credit. Data science principles have been applied not only to customer acquisition, but to customer retention as well. When a customer calls looking for a better deal, data-driven models calculate the potential profitability of various possible actions (different offers, including maintaining the status quo) and the customer service representative's computer comes up with the best deals to make.

According to BARBIERI (2020) the passage of data from the transactional environment (HR, Financial, Sales Systems) to the informational environment requires an assessment regarding the quality of its structure and content. After all, there are statistics that point out that data with low quality can lead to losses between 15% and 25% of the company's revenue. A quality look is essential, as this is the time to prepare data so that top management can make critical decisions. Also, according to BARBIERI (2020) the concept of data quality is based on formal definitions of precision, accuracy (accuracy), integrity, availability, completeness, etc.

5.1 Tools

For SHARDA (2019) the pillars of modern management are based on data analysis and BI tools such as “data storage, data mining, online analytical processing (OLAP), dashboards and use of cloud-based systems for decision support”, he also lists networks of high-speed computerized systems to help managers in their most important task, which according to him is making decisions.

The figure below presented by SHARDA (2019) demonstrates the various tools, functionalities and techniques that can be included in a BI system, in addition to presenting the evolution of BI.



Source: (SHARDA, 2019)

SHARDA (2019) adds to this tool framework statistical modeling for statistical analysis business which is used for business analysis. It he comes attracting commercial users, statisticians, and data analysis professionals as an evidence-based decision support tool.

Tools with big data, data mining, machine learning, deep learning, artificial intelligence (AI) and data viz (data visualization) are available so that professionals involved in analysis can make the most of the data.

5.2 Count on qualified analysis who understand the technologies and the business

Far beyond computers, software and reports, people who carry out the analyzes are needed to carry out the analysis work and are scarce resources today in organizations LOPES (2016). LOPES (2016) also states that: “it takes an intelligent human being to interpret the identified patterns, validate, confirm and translate them into new insights and recommendations so that other intelligent human beings actually take some action”. In this sense, the author himself emphasizes that: “in addition to committed executives, most organizations oriented to data and analysis have a group of intelligent and hardworking analytical professionals within their organizations”.

5.3 Culture

One of the pillars driving the evolution of an organization that is still on the basis of traditional BI to an organization that uses data extensively to make decisions is its culture. In a recent interview for Mckinsey , conducted by DELALLO (2019), Sam Yagan CEO of ShopRunner and former CEO of Match Group, underscores the importance of a data-driven approach mentioning that as soon as he became CEO of ShopRunner he made it clear that everyone would take decisions influenced by the data, knowing that not everyone fit into the company's culture anymore and that when hiring people, experience in data would be used as a filter for selection. Candidates were asked how they used data in the past to make current decisions, also pointing out the importance of decision-making based on data by the executive team, as this facilitates the implementation of the culture, as all other workers in the organization will mirror them . WALLER (2020) reports that the biggest issues for implementing data-based businesses are not technical but cultural, that changing mindsets presents itself as a daunting challenge. Companies that already have their Data- Driven culture tend to have top managers who encourage decisions to be anchored in data, so the culture starts at the top. According to WALLER (2020) a powerful effect can be exerted through leaders when they skillfully choose what should be measured and which metrics they encourage employees to use, so the choice of metrics is also fundamental for implementing a data-based culture . Bringing the data professional into the business is an important strategy. The BA will not survive or bring value if it is separated from the rest of the business areas, and that it is necessary to share business knowledge and technical know-how, because by bringing data science closer to the business, it is drawn to data science, especially when insisting that employees are literate in Business Analytics WALLER (2020). For FAWCETT (2018) employees from all units must interact with the data scientist team, because if they do not have “a fundamental basis in the principles of data analytical thinking, they will not really understand what is happening in the company” .

Democratizing access to data within organizations is critical, as analysts need data to create lots of analyzes and without them data- driven culture is impossible to take root and grow.

WALLER (2020) points out that working with security measures is a fundamental step and that teams are explicit and quantitative about the degree of confidence in the information to mediate the level of uncertainty and verify whether the data is reliable. Knowing the degree of uncertainty helps analysts to have a better understanding of the model used and leads the company to carry out experiments to verify the degree of accuracy of its data and models.

Start small, simple but robust and only then increase your level of sophistication. WALLER (2020) points out that it is important to create simple and robust proofs of concept. Indicate which training should be offered at the right time so that employees do not quickly forget what they have learned if they do not put it into practice quickly.

The analytics should also help the company's employees, not just the customers, benefiting them from using BA so they can, for example, save time, avoid rework, or look up frequently needed information. Be careful with flexibility, as what WALLER (2020) calls “data tribes” are often harmful to the organization since a lot of effort must be spent to equalize slightly different versions of a metric that should be universal.

6. INFORMATION ANALYSIS

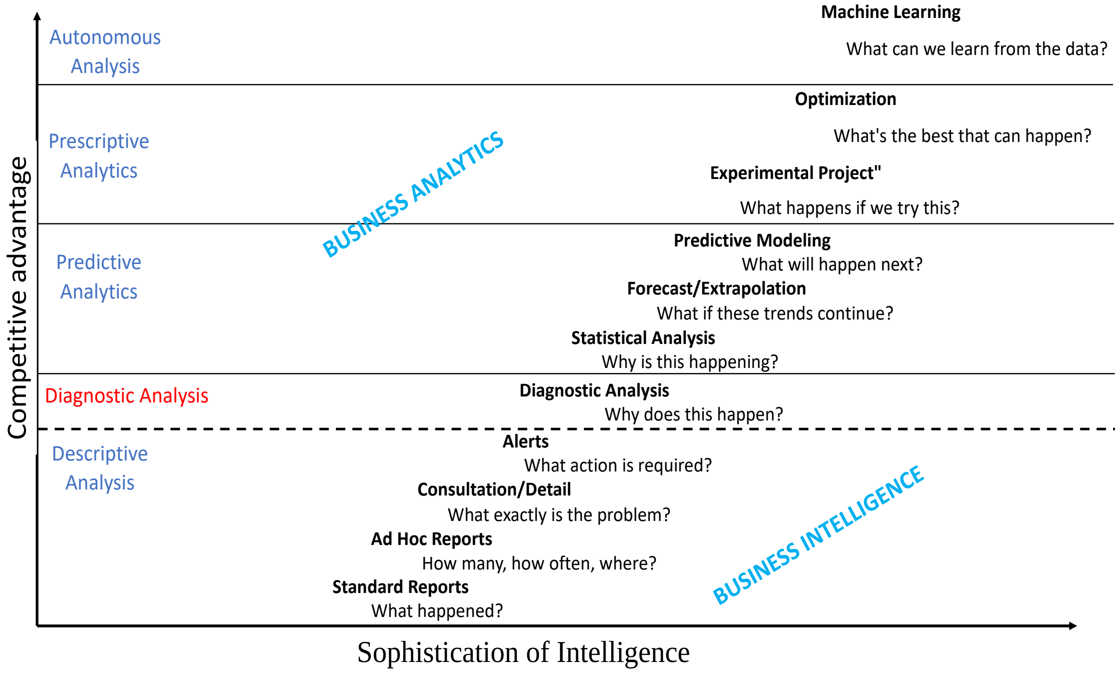
Although some authors differ in the definition of BI and BA, whether they are different concepts and methods or not, most agree that BA is an evolution of BI and that BA uses past data to create trends and forecasts.

For SHARDA (2019) the generation of forecasts and trend analysis can be characterized within the BI process, as according to him, suppliers and researchers use the term BI to refer to such analyses. For the author, “although most people would probably agree that BI has evolved to become data analysis and data science, many vendors and researchers still use this term.”. The author reports that in the mid-2000s, BI systems incorporated artificial intelligence functionalities and powerful analytical resources.

DAVENPORT (2018) makes a clear separation between the concepts of BI and BA, describing BI as the system that looks at historical facts, using mainly descriptive analysis, and BA as an evolution of BI, using these historical data present in BI to through predictive analytics “looking” into the future. SAHAY (2018) shares Davenport's view and points out that BI analyzes historical data while BA deals with future trends.

The chart below is a slight adaptation of DAVENPORT's view (2018) as it includes the diagnostic analysis among the analyzes and describes them in well-defined phases where any organization can mirror itself to carry out the migration from BI to BA, increasing its degree of maturity in data analysis.

Graph 1: The potential for competitive advantage increases with more sophisticated analysis



Source: (Adapted from Davenport, 2018)

The graph presents a well-defined journey towards the evolution of data analytics maturity. As BI is the basis for BA, companies that have not yet started their journey in data analysis must go through the whole journey from a analysis descriptive . However, for those organizations that have already started, they should check what stage they are in their data race and evolve to the next level and observe to the phases and assumptions described below.

Maturity	Phase	Toll	Feature
Analysis 4.0	Machine Learning	BA	Cognitive Analysis
Analysis 3.0	Analytics	BA	Predictive and Prescriptive Analytics
Analysis 2.0	Big Data	BI/BA	Structured and Unstructured
Analysis 1.0	Business Intelligence	BI	Structured Data

Source: (Adapted from Davenport, 2018)

Table 1 - Maturity between stages for evolution in BA

Premises:

- Data as a active organizational ;
- Tools suitable ;
- Guys qualified ;
- Organization culture .

Observing the phases and assumptions is a method for organizations to be able to structure themselves to go through the journey of evolution towards the BA.

7. CONCLUSIONS AND FUTURE WORK

Just looking at the past no longer guarantees organizations a competitive advantage in the market in which they operate. In this scenario, the use of BI alone does not guarantee a decision-making process in which managers achieve goals and achieve objectives. For this to be possible, it is essential to use all the potential that data has with BA, an evolution of BI generating forecasts and trends for the future, giving managers a clear direction for decision making. It is in this sense that the research answers the question of the proposed problem and reports that in the era of digital transformation, the evolution to the BA is fundamental to understand how the future of the company, its results and its development unfolds. Permanent assessment allows you to act "before the storm", not anticipating deviations in the path in a timely manner can lead to the compromise of the entire business. That is why it is essential to analyze scenarios on an ongoing basis, to evaluate events that occurred in the past in order to discover trends to correct the course. Business Analytics is able to identify and inform so that the manager can take the necessary measures before the problem worsens. Working constantly with the BA will help the manager to make decisions before the effective implementation of the problem. It is essential to point out some limitations in the study method, since neither BI nor BA can help in decision-making in isolation, but together with value engineering tools and/or blueprint of a data-based solution, which suggests It is therefore hoped that this will be studied in future work.

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